Original Paper

ASSETs for Aging in Place: 12-Month Descriptive Longitudinal Study of Technology-Supported Interprofessional Care Coordination After Nursing Home Discharge

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Abstract

Background: Older and disabled adults face ongoing barriers to aging in place (AIP) after nursing home discharge, particularly following the end of time-limited transition programs. Sustained care coordination and early detection of health and functional changes remain limited, especially in rural and underresourced communities.

Objective: This study aimed to evaluate the feasibility of technology-enabled interdisciplinary care coordination among older and disabled adults enrolled in the ASSETs (Age-Friendly Smart, Sustainable, and Equitable Technologies) for AIP program and to descriptively characterize changes in quality of life (QoL), function, and cognition over 12 months.

Methods: This quantitative, descriptive study used repeated measures over 12 months among older and disabled adults 1 year postdischarge from Missouri's Show-Me Home program. An interdisciplinary team (registered nurse [RN], occupational therapist [OT], and social worker [SW]) provided remote care coordination supported by open-source smart home sensors, consumer-grade wearable devices, and telehealth. Outcomes were assessed quarterly using the interRAI home care (HC) assessment and the Money Follows the Person (MFP) QoL survey.

Results: Nineteen clients were included. Sensor and wearable data were used for remote monitoring, identification of changes in activity patterns, and care coordination. Across repeated assessments, no statistically significant declines were observed in functional status, cognitive performance, instrumental activities of daily living (IADL), or quality-of-life measures. Reports of unmet medical care needs decreased across follow-up.

Conclusions: This study supports the feasibility of a digital health–enabled, interdisciplinary care coordination program using cost-feasible open-source and consumer-grade technologies. Preliminary findings indicate that no statistically significant decline in function or quality-of-life measures was observed during follow-up. Larger-scale implementation is needed to further evaluate effectiveness and refine data-driven care coordination workflows for underserved populations.

(JMIR Aging 2026;9:e91524) doi: 10.2196/91524

KEYWORDS

aging in place; quality of life; care coordination; wearable sensors; rural health; interRAI

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Introduction

Background

In the United States, one-third of individuals will live in a nursing home at some point in their lives, with nursing home admission often following hospitalization for an acute illness [1,2]. While it is difficult to quantify how many older adults will remain permanently in the nursing home following a hospitalization, Xu et al [3] found that only 29% of individuals admitted to the nursing home for a short stay successfully returned home with few readmissions to the nursing home or hospital. Older and disabled adults face significant barriers to maintaining independence at home following nursing home discharge, including limited access to services and caregiver networks. These barriers are heightened for individuals managing multiple chronic conditions, functional limitations, or limited mobility [4,5]. Successful aging in place (AIP) often depends on early identification of changes in health and timely intervention. Technology-enhanced care coordination can help identify and respond to health status changes, yet few individuals residing in their own homes have access to these services [2,6]. The lack of infrastructure to support remaining at home is particularly challenging in underresourced areas where limited financial, technological, and human resources hinder the adoption of systems that enable early detection and intervention [7,8].

In the United States, federal programs such as Medicare and Medicaid provide health insurance to eligible Americans. Medicare is primarily for older adults aged older than 65 years; however, younger individuals with disabilities may be eligible [9]. Medicaid is a joint federal-state insurance program for low-income Americans, covering about 1 in 5 people, including the older adults and adults with disabilities [9]. The Money Follows the Person (MFP) Initiative, known in Missouri as the Show-Me Home program, provides enhanced Medicaid funding to support individuals for up to 1 year who wish to transition from nursing homes or other institutional settings back into the community. Through this program, clients may access transition coordination, housing support, and home and community-based services designed to reduce reliance on institutional care and improve quality of life (QoL) [10-12]. However, when individuals are discharged from the Show-Me Home program, the risk for nursing home readmission re-emerges as a potential problem; this is particularly concerning for clients who do not meet criteria for home and community care services, as they have fewer community supports. To address these gaps, we launched the ASSETs (Age-Friendly Smart, Sustainable, and Equitable Technologies) for AIP demonstration project [13]. ASSETs for AIP is a digital health program that relies on an interdisciplinary team to provide sensor-enhanced care coordination to support and maintain independence for low-income older adults discharged from nursing homes back to the community. This study examines changes in QoL over 12 months for older adults enrolled in the ASSETs for AIP program and describes how sensor data are used by the care coordination team to support AIP.

AIP

AIP emphasizes supporting older adults' ability to live safely and independently in their homes and communities by leveraging individual strengths, environmental support, and coordinated services. Care coordination is the process of organizing care activities a person receives and sharing information among all clients involved to facilitate appropriate delivery of services [14]. Interdisciplinary care coordination models are central to AIP and integrate nursing, social work, occupational therapy, and community-based resources to address health, functional, and psychosocial needs in a holistic manner [14,15]. Rather than focusing solely on deficits, strengths-based approaches empower older adults to identify personally meaningful goals, actively participate in care planning, and build self-efficacy in managing chronic conditions and functional limitations [16]. When older adults are supported by coordinated, home-based interdisciplinary teams, early identification of health and functional changes can lead to timely interventions that reduce disability, improve QoL, and promote sustained independence [17].

Multicomponent biobehavioral interventions for older adults at home, such as CAPABLE (Community Aging in Place—Advancing Better Living for Elders) [18-20] and STAReD (Smart Technology for Aging and Reducing Disability) [21], have shown improvements in functional outcomes, safety, and health-related QoL, underscoring the value of interdisciplinary, community-based models that align clinical expertise with older adults' goals and lived environments [22]. Digital health technologies (eg, smart home sensor systems, wearable devices including smartwatches and rings, and telehealth [23]) further enhance care coordination by providing objective, longitudinal data on daily activities, mobility, and health-related metrics (eg, heart rate), enabling teams to detect subtle changes before they escalate into adverse outcomes [13,21]. When deployed to support community-based, strengths-focused care coordination frameworks, these technologies support proactive, person-centered decision-making while preserving autonomy and dignity.

Building on these principles, a series of aging-in-place initiatives at the University of Missouri (MU) have explored how interdisciplinary care coordination and technology-enabled monitoring support long-term community living among older adults. These programs provided the conceptual and operational foundation for the development of ASSETs for AIP. Changes in health conditions in older adults, if caught early, can be managed or reversed. In 1996, the AIP team at the MU developed and tested the AIP care coordination model in frail older community-dwelling adults [24,25]. When compared to older adults who received AIP care coordination and those who received traditional home health care, those in AIP care coordination were significantly older, Medicaid recipients, lived alone, had worse cognitive impairment and depression, and had worse activities of daily living (ADL) and instrumental ADL scores [26]. Yet when compared to outcomes of the home health care group, those in the AIP group had lower rates of ADL and instrumental activities of daily living (IADL) decline, fewer rehospitalizations, and lower provider and outpatient costs, but not in overall costs. In 2004, the community-based care model

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transitioned to TigerPlace, a public or private partnership with Americare in an independent living with services facility [27]. TigerPlace was the first test site for in-home environmentally embedded sensors used for frail older adults to identify early illness and detect functional decline. Automatically generated sensor-based health alerts identify illness days or weeks earlier than people realize they are ill, allowing them to seek health care services earlier [28-31]. Additionally, living in an environment with sensor technology with health alerts added an average of almost 2 (1.7) years to older adults' length of stay in Independent Senior Housing. When combined with registered nurse (RN) care coordination, sensor technology with health alerts increased length of stay in independent senior housing by an additional 2.5 years, from 1.8 to 4.3 years [32]. A longitudinal analysis of the impact of AIP TigerPlace when compared to a reference group from 2011 to 2019 showed stable functional trajectories, with costs just above residential care costs [33]. While these prior initiatives demonstrated the potential of interdisciplinary care coordination and sensor-enabled monitoring, additional work was needed to develop a scalable, cost-feasible model capable of supporting individuals transitioning from institutional care back to community settings across geographically dispersed and resource-limited environments.

ASSETs for AIP

ASSETs for AIP used the conceptual framework described in the Agency for Healthcare Research and Quality (AHRQ) Care Coordination Atlas to operationalize the care coordination activities used by the interdisciplinary team [14]. The care coordination atlas identifies broad approaches to care coordination, including teamwork-based coordination and health IT-enabled coordination [14]. Care coordination activities provided by ASSETs broadly aligned with the 9 AHRQ care coordination domains, including (1) establishing accountability and negotiating responsibility; (2) communicating; (3) facilitating transitions; (4) assessing needs and goals; (5) creating a proactive plan of care; (6) monitoring, follow-up, and responding to change; (7) supporting self-management goals; (8) linking to community resources; and (9) aligning resources with client needs [14]. ASSETs for AIP uses a team-based care coordination informed by prior aging-in-place, sensor-based monitoring, and community-based intervention research. Services were delivered by an interdisciplinary team consisting of an RN, an occupational therapist (OT), and a social worker (SW). The RN addressed health-related concerns, medication management, and care coordination; the OT focused on home safety, functional independence, and environmental adaptations; and the SW facilitated access to community resources and provided psychosocial support. Team members collaborated closely, shared knowledge of all clients, and worked interchangeably as needed to ensure continuity of care.

ASSETs for AIP provided ongoing interdisciplinary care coordination. The program integrated standardized assessments, telehealth encounters, wearable devices, and ambient smart home monitoring to support early identification of changes in health (eg, heart rate), function (ambulation), and daily activity patterns (time spent in rooms). These data were reviewed by the care coordination team and used to inform client coaching to support client-identified goals for health and function. Additionally, clients were provided simple home safety equipment (eg, bath mats and movement-sensitive light switches) to improve their environment and make their homes more livable. All communication was intended to provide client support to enable them to communicate their needs effectively to service and health care providers so they could continue to live in their community homes and meet their personal goals.

Technology Overview

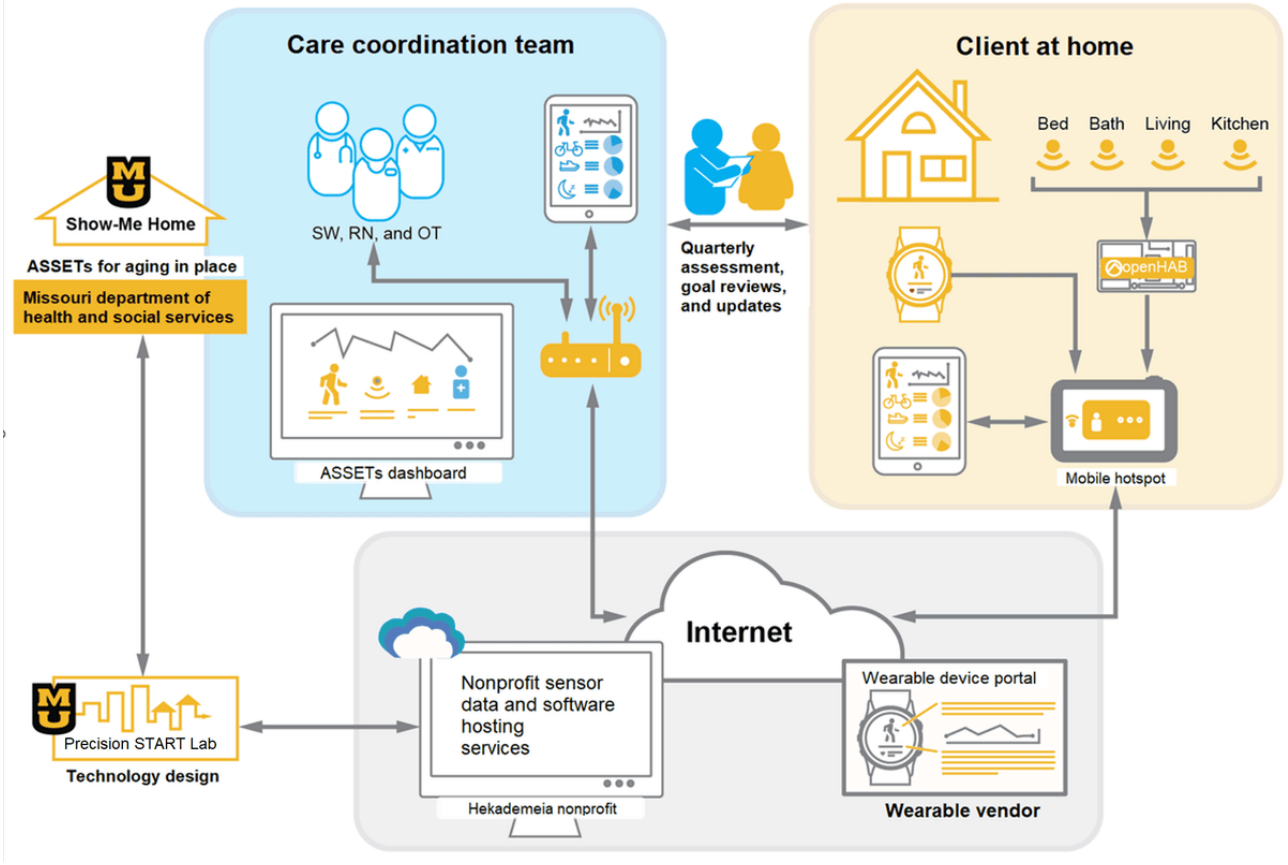
Overview

ASSETs for AIP technologies were selected, developed, configured, and evaluated at the Precision START laboratory [34-37] at the MU Sinclair School of Nursing during and after conceptualization of the program (Figure 1). This selection and test process relied on a *Translation by Design* approach [38] that prioritizes cost-feasibility and adaptability to maximize long-term sustainability and maintenance following implementation. To overcome sustainability issues experienced during previous sensor research to support AIP [39-42], our focus was on identifying free open-source software technologies and widely available consumer-grade devices selected through rapid evaluation processes [34,37]. Low-cost web-based application and data hosting and support for the smart home system are provided by a nonprofit organization created specifically for this purpose [43,44].

System components are a smart home sensor system, a smart home sensor dashboard and data services, a tablet device, and a wearable device.

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Figure 1. Workflow of ASSETs for AIP (aging in place). ASSETs: Age-Friendly Smart, Sustainable, and Equitable Technologies; MU: University of Missouri; OT: occupational therapist; RN: registered nurse; SW: social worker.



Smart Home Sensor System

This technology component consisted of a low-cost Raspberry Pi computer running open-source home automation software (openHAB) connected to consumer-grade environmental sensors that capture room-level and light levels.

Smart Home Sensor Dashboard and Data Services

This technology component is a web-based application developed in-house and hosted by the nonprofit service provider [35]. Sensor data are uploaded to individual client accounts and viewed through a dashboard that supports monitoring of system status and home activity patterns. Dashboard information was used as 1 source of information to support follow-up decisions and was interpreted in conjunction with client reports, assessments, and clinical judgment rather than relying on predefined automated alert thresholds.

Tablet Device

Participants were provided with a low-cost tablet to support technology and enable telehealth visits with the remote care coordination team. For troubleshooting after deployment, we used the remote access feature of the device to troubleshoot sensor connection issues.

Wearable Device

Participants were provided with a consumer-grade wearable device (eg, smartwatch or smart ring) to support activity monitoring and self-management.

Internet Connectivity

Broadband internet access was provided through a wireless mobile hotspot when needed for program participation.

The ASSETs for the AIP demonstration project connected older adults at home to interdisciplinary care coordination across geographic distances using the digital health technologies above in the section Technology Overview.

Methods

Study Design

This is a quantitative, descriptive study with repeated measures over 12 months.

Recruitment

Client Eligibility

Eligibility criteria for the ASSETs for the AIP program included older adults and adults with disabilities who were within 1 year of discharge from the Show-Me Home program in Missouri. The Show-Me Home program serves both older adults and younger adults with disabilities transitioning from institutional care back into the community. Accordingly, the study population reflected the underlying population served by the Show-Me Home program. Administrators at the state informed the team about recent discharges and who should be contacted about enrollment into ASSETs for AIP. Those eligible were then contacted via phone to determine interest. No technology experience was required, and all equipment, connectivity, and

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training were provided by the program. Participant recruitment and enrollment occurred on a rolling basis between April 2022 and December 2025. Participants were followed quarterly for the duration of their enrollment in the ASSETs for AIP.

Recruitment Strategies

A client list was provided by Show-Me Home to the ASSETs for the AIP team. This list was based on contact information collected at client discharge from the Show-Me Program. Once the team received the list, they began recruitment. Despite diligent efforts, the team encountered challenges including the following: (1) locating individuals who were more than one year postdischarge from a state-funded program; (2) working within a limited-service area; (3) once reached, getting clients to respond about a new, unknown program; and (4) inaccurate or obsolete contact information. Successful strategies included partnering with state and local agencies to retrieve up-to-date contact information, reducing the time from Show-Me Home program discharge to facilitate contact and align better with client needs, extending the service area beyond the mid-Missouri area, including larger urban areas, and sending out postcard mailers to potential clients that provided a clear linkage between the Show-Me Home program, ASSETs for AIP, and MU. Following implementation of the revised recruitment strategies, client enrollment increased by 225% over the subsequent 6 months. Participant flow from screening through final analysis is summarized in Table 1.

Table 1. Participant flow from screening through final analysis.

Participant flow stage	Values, n
Total number of individuals contacted	406
Screened	58
Excluded after screening	13
Enrolled	45
Discharge during study[a]	11
Participant request or withdrawal	5
Limited availability or relocation	1
Diminishing returns	2
Technology loss or noncompliance	2
Incarceration	1
Primary analytic cohort with complete longitudinal assessments	19
Enrolled for MFP[b] quality of outcome item C4 analysis only[c]	1
Enrolled but not included in the analysis (<4 time points at the time of analysis)	25

[a]Discharge during the study did not necessarily result in exclusion from analysis. Participants who were subsequently discharged were included in outcome-specific analyses if they had completed the admission assessment and 4 quarterly follow-up assessments for that outcome.

[b]MFP: Money Follows the Person.

[c]One additional participant outside the primary analytic cohort had complete longitudinal data (admission through quarter 4) for the unmet medical need outcome and was included only in that outcome-specific analysis.

Care Coordination Team Support

The RN, OT, and SW care coordination team collaborated to deliver coordinated care by conducting remote and in-home assessments, setting person-centered goals, and reviewing sensor and wearable data to monitor health status and daily function. The team conducted a full assessment upon client admission using REDCap surveys, an in-home visit for equipment setup, and a home safety checklist. A shorter assessment followed every quarter using selected items. Health data from ambient and wearable sensors, displayed on a cloud-based visual dashboard, were used by the team to monitor clients' activity patterns. The team reviewed the dashboards daily to respond quickly to changes, including reduced activity from ambient sensors or shifts in heart rate and step data from wearable devices. Using information from the assessment and sensor data, the team contacted the client to discuss changes, agreed on a plan of action when needed, and coached the client as to what the next steps could be. This approach let the team monitor the client from a distance and connect by tablet or phone when activity changes suggested the need for further evaluation. The care coordinators did not directly intervene with the clients and their individual health care team but rather coached the client as to what they should be doing next and followed up to support the client as needed.

Data Collection

The interRAI home care (HC) assessment [45-47] is a validated and standardized tool designed to evaluate the health, functional, and psychosocial status of individuals receiving HC services. It provides a comprehensive framework for care planning and monitoring outcomes, using validated scales to assess key domains such as daily functioning and cognition. Participants with sufficient longitudinal data for a given outcome, defined as an admission assessment and 4 quarterly follow-up assessments for that outcome, were included in the

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corresponding analysis. Consequently, analytic sample sizes varied (range n=16-20) across outcomes based on outcome-specific data completeness. All interRAI HC and MFP QoL assessments were administered in person during scheduled quarterly client visits. Assessments were completed by members of the interdisciplinary care coordination team, including RNs, OTs, and SWs. Care coordinators received training on assessment administration and program procedures before conducting client assessments to promote consistency in data collection.

ADL Hierarchy Scale

The ADL Hierarchy Scale [46] reflects the disablement process by grouping ADL into stages of functional decline: early (personal hygiene), middle (locomotion, toileting), and late (eating). It uses 4 self-performance items coded over the prior 3 days, with scores ranging from 0 (independent) to 6 (total dependence), where higher scores indicate greater functional loss.

Cognitive Performance Scale

The Cognitive Performance Scale (CPS) [47-49] measures cognitive status using items related to decision-making, short-term memory, communication, and eating performance. It produces a score from 0 (intact) to 6 (very severe impairment). The CPS has been validated against cognitive assessments such as the Mini-Mental State Examination (MMSE) and the Test for Severe Impairment (TSI). The MFP QoL Survey was also administered quarterly.

Analysis

Overview

Given the exploratory nature of this demonstration project and the modest sample size, analyses were conducted to characterize cohort-level longitudinal patterns rather than evaluate program effectiveness or estimate individual-level trajectories. For the interRAI outcomes, client scores were summarized across all clients at each assessment period (admission and quarterly follow-ups), and weighted linear regression was used to examine overall cohort-level trends over time. For the MFP QoL measures, repeated-measures nonparametric tests were used to evaluate changes across assessment periods. The objective was to describe overall trends among clients with complete longitudinal data rather than estimate individual-level trajectories or intervention effects. Analyses were conducted using available data, and no imputation procedures were performed. Differences in outcome-specific sample sizes reflected item-level nonresponse within individual MFP QoL survey items.

interRAI: ADL Hierarchy Scale and CPS

ADL Hierarchy Scale and CPS scores were first summed across clients at each time point (n=19) to produce mean and SD values. To assess overall trends, we fitted weighted linear regression models of mean score on timepoint, with weights calculated as the inverse of the variance ($1/SD^2$) at each timepoint. Slope estimates and CIs were used to evaluate whether ADL or CPS scores showed systematic change over time.

interRAI: IADL Functional Outcomes

The interRAI functional items (C2a-d: managing finances, managing medications, managing use of electronic devices, and managing online shopping or ordering; G4a-e: meal preparation, ordinary housework, stairs, shopping, and transportation) were combined to represent overall functional independence in instrumental and domestic activities. At each assessment, each client received a composite IADL functional score by summing responses across the 9 interRAI functional items. The client-level composite scores were then averaged across all clients to obtain a single mean score for each assessment period (admission and quarters 1-4). Weighted linear regression was performed using these 5 mean scores, with weights calculated as the inverse of the variance ($1/SD^2$) at each timepoint, to characterize overall trends over time.

MFP QoL Survey

Analyses were conducted to examine changes in outcomes across 5 repeated assessments (admission and quarters 1-4). For ordinal and continuous outcomes, including satisfaction with living arrangements, life satisfaction, satisfaction with care received, choice and control of daily activities, and sleep quality, we used the Friedman test for nonparametric repeated measures. To adjust for multiple comparisons, a Bonferroni correction was applied across the 4 admission–quarter contrasts. For binary outcomes, including respect and dignity, unmet need for personal assistance, and unmet need for medical care, the Cochran Q test was used to assess overall change across time points. In addition, McNemar exact tests were performed for pairwise admission-quarter comparisons. All tests were 2-tailed with a significance threshold of $P<.05$.

Ethical Considerations

The study of ASSETs for AIP was approved under MU Health Sciences IRB (#2080782). Research consent was obtained via phone call, followed by an in-person home visit.

Results

Participant Characteristics

Nineteen clients comprised the primary analytic cohort (Table 2). Outcome-specific analytic sample sizes varied according to longitudinal data completeness, as described in the Methods. Most were aged 61 to 80 years, female, divorced, and White. Household income was low, with the majority reporting annual incomes between US $10,000 and US $19,999. Nearly all clients had Medicaid, and over two-thirds also had Medicare. Slightly more than half reported no availability of at-home health care assistance. Falls were uncommon across all assessed periods, with most clients reporting no falls in the prior 30, 31 to 90, or 91 to 180 days. Only 1 client experienced a fall with major consequences within the last 90 days. Comorbidity burden was high. Depression was the most prevalent condition, followed by type 2 diabetes, vascular disease, anxiety, and stroke or cerebrovascular accident. Multiple neurologic, cardiopulmonary, and psychiatric conditions were also reported, indicating substantial multimorbidity within the sample.

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Table 2. Participant characteristics (N=19).

Variable	Values, n (%)
Age (years)[a]	
40-60	6 (32)
61-80	13 (68)
Gender	
Male	8 (42)
Female	11 (58)
Marital status	
Divorced	13 (68)
Widowed	4 (21)
Never married	2 (11)
Race	
White	14 (74)
Black or African American	4 (21)
Multiracial[b]	1 (5)
Annual household income (US $)	
<$10,000	2 (11)
$10,000-$19,999	12 (63)
$20,000-$29,999	4 (21)
Preferred not to answer	1 (5)
Health insurance[c]	
Medicaid	18 (95)
Medicare	13 (68)
Availability of at-home help for health care	
Yes	9 (47)
No	10 (53)
Falls	
In the last 30 days	
No falls	15 (79)
One fall	4 (21)
In the last 31-90 days	
No falls	15 (79)
One fall	3 (16)
Two or more falls	1 (5)
In the last 91-180 days	
No falls	15 (79)
One fall	3 (16)
Two or more falls	1 (5)
Any fall with major consequences within the last 90 days	
Yes	1 (5)
No	18 (95)
Morbidity[d]	

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Variable	Values, n (%)
Psychiatric diseases	
Depression	11 (58)
Anxiety	7 (37)
Posttraumatic stress disorder	4 (21)
Bipolar disorder	2 (11)
Schizophrenia	1 (5)
Cardiometabolic diseases	
Type 2 diabetes mellitus	9 (47)
Vascular disease	8 (42)
Chronic obstructive pulmonary disorder	5 (26)
Coronary heart disease	3 (16)
Heart failure	3 (16)
CKD[e]	1 (5)
Neurologic diseases	
Stroke or CVA[f]	6 (32)
Hemiplegia	5 (26)
Aphasia	5 (26)
Neuropathy	4 (21)
Seizure	3 (16)
Traumatic brain injury	3 (16)
Multiple sclerosis	1 (5)
Other	
Cancer	3 (16)
Urinary tract infection during the last 30 days	2 (11)
Other fractures during the last 30 days	1 (5)
COVID-19 diagnosis in the last 90 days	1 (5)

[a]Mean 64, SD 10.7.

[b]Multiracial here includes the following races: Black or African American and American Indian or Alaska Native.

[c]Participants may have either Medicare and Medicaid or both.

[d]Participants had been diagnosed with the listed comorbidities; some were undergoing active treatment, while others were being monitored without active treatment.

[e]CKD: chronic kidney disease.

[f]CVA: cerebrovascular accident.

interRAI

ADL Hierarchy Scale

Mean ADL scores were very low at admission and remained low across all 5 time points (Figure 2 and Table 3). The fitted linear trend was essentially flat, with a slope estimate of −0.0185 per time point (SE 0.0738; t_3=−0.25, P=.82). The 95% CI for the slope (−0.253 to 0.216) included 0, indicating no evidence of a systematic increase or decrease in ADL scores over time. The overall conclusion is that ADL scores remained stable. The data are consistent with a small negative trend, no trend, or a small positive trend.

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Figure 2. ADL Hierarchy Scale and Cognitive Performance Scale. ADL: activities of daily living; CPS: Cognitive Performance Scale.

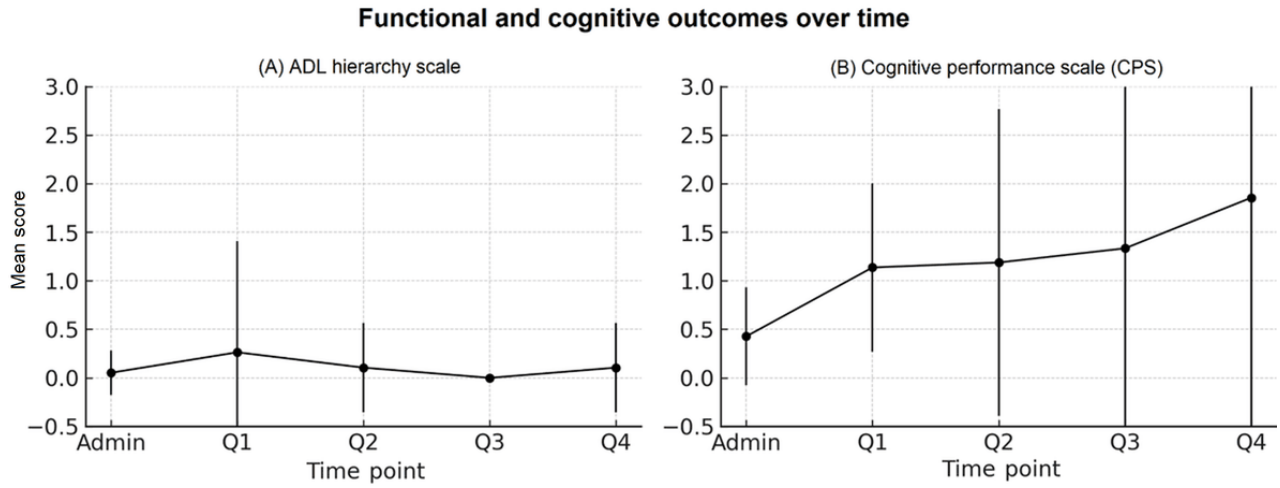


Table 3. Summary of interRAI subscales and IADL[a] outcomes across time points. Means and SDs are aggregated across clients at each time point (admission, quarters 1-4).

Measure	n	Admit	Q1[b]	Q2	Q3	Q4	Slope (per quarter)	
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Slope (95% CI)	*P* value
ADL[c] Hierarchy Scale	19	0.05 (0.23)	0.26 (1.15)	0.11 (0.46)	0.00 (0.00)	0.11 (0.46)	−0.0185 (−0.253 to 0.216)	.82
CPS[d]	19	0.43 (0.50)	1.14 (0.87)	1.19 (1.58)	1.33 (2.31)	1.85 (2.73)	0.390 (−1.03 to 1.81)	.45
interRAI functional items (C2[e], G4[f])	19	17.21 (11.17)	18.63 (11.66)	16.32 (11.76)	16.63 (10.98)	15.11 (11.23)	−0.608 (−11.90 to 10.68)	.875

[a]IADL: instrumental activities of daily living.

[b]Q: quarter.

[c]ADL: activities of daily living.

[d]CPS: Cognitive Performance Scale.

[e]C2: managing finances, medications, using electronic devices, and shopping or ordering online.

[f]G4: assessing instrumental activities of daily living capacity, including meal preparation, routine housework, stair navigation, shopping, and transportation.

CPS

Mean CPS scores increased from 0.43 (SD 0.50) at admission to 1.85 (SD 2.73) at quarter 4, with SDs also increasing across time points (Figure 2 and Table 3). A weighted regression of CPS scores on time indicated a positive slope estimate of 0.39 per time point (SE 0.45 t_3=0.88, *P*=.45). The 95% CI for the slope (−1.03 to 1.81) was wide and included 0, indicating no statistically reliable evidence of an upward trend. Overall, these data are compatible with no change or with small increases or decreases in CPS over time and do not support a conclusion of systematic cognitive decline during follow-up.

IADL Functional Items

The summed score across the 9 interRAI functional items (manage finances, manage medications, manage use of electronic devices, manage online shopping or ordering, meal preparation, housework, stairs, shopping, and transportation) showed mean values of 17.21 (SD 11.17) at admission, 18.63 (SD 11.66) at Q1, 16.32 (SD 11.76) at Q2, 16.63 (SD 10.98) at Q3, and 15.11 (SD 11.23) at Q4 (Table 3). The 9 functional items were summed to create an overall functional independence score, with higher scores indicating greater functional impairment. Weighted linear regression of mean score on time point yielded a slope of −0.61 per quarter (SE 3.55; t_3=−0.17, *P*=.875; 95% CI –11.90 to 10.68). These data show that there is no evidence of systematic improvement or decline in functional outcomes over time.

MFP QoL

Satisfaction With Living Arrangements

At admission, 15 of 19 (78.9%) clients reported being satisfied, and this proportion remained high through follow-up (Q1=84%, 16/19; Q2=84%, 16/19; Q3=90%, 17/19; and Q4=84%, 16/19; Table 4). A Friedman test indicated no significant differences across time (χ^2_4=3.34, *P*=.50). Paired Wilcoxon signed-rank tests comparing admission to each quarter were all nonsignificant after Bonferroni correction. Trends are displayed in Figure 3.

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Table 4. Summary of MFP[a] quality of life outcomes across time points[b].

Domain	Admission	Q1[c]	Q2	Q3	Q4	Test	
	n/N (%)	n/N (%)	n/N (%)	n/N (%)	n/N (%)	Values	*P* value
A. Living arrangements	15/19 (79)	16/19 (84)	16/19 (84)	17/19 (90)	16/19 (84)	3.34[d]	.50
B. Life satisfaction	18/19 (95)	15/19 (79)	16/19 (84)	18/19 (95)	15/19 (79)	8.36[d]	.08
C1. Care satisfaction	18/19 (95)	15/19 (79)	17/19 (90)	17/19 (90)	18/19 (95)	3.75[d]	.44
C2. Respect and dignity	15/16 (94)	14/16 (88)	16/16 (100)	15/16 (94)	16/16 (100)	4.00[e]	.41
C3. Unmet personal assistance need	1/19 (5)	2/19 (10)	1/19 (5)	1/19 (5)	1/19 (5)	4.00[e]	.41
C4. Unmet medical need	5/20 (25)	4/20 (20)	1/20 (5)	1/20 (5)	0/20 (0)	10.44[e]	.03
D. Choice and control	5.97 (0.12)[f]	5.85 (0.49)[f]	5.94 (0.24)[f]	6.00 (0.00)[f]	6.00 (0.00)[f]	4.56[d]	.34
E. Sleep quality	16/19 (84)	16/19 (84)	17/19 (90)	18/19 (95)	18/19 (95)	7.56[d]	.11

[a]MFP: Money Follows the Person.

[b]Values are percentages of clients reporting the specified outcome. Analyses were conducted using available data without imputation. Sample sizes vary across outcomes because of outcome-specific missing data. Three participants did not complete the MFP quality of life C2 assessment; therefore, C2-derived outcomes included 16 participants. One additional participant had complete administrative privileges through Q4 data for the unmet medical needs outcome but did not have complete Q4 data for the other MFP quality of life domains; therefore, this outcome included 20 participants.

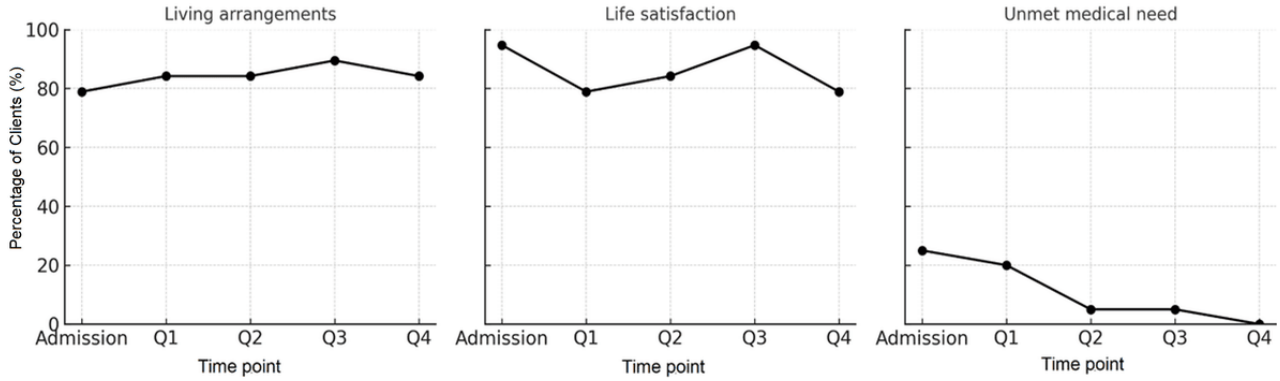
[c]Q: quarter.

[d]Friedman χ^2.

[e]Cochran Q.

[f]Mean (SD).

Figure 3. Key outcomes over time: living arrangements, life satisfaction, and unmet medical need.



Life Satisfaction

A Friedman test was performed but did not reach significance (χ^2_4=8.36, *P*=.08). Pairwise Wilcoxon signed-rank tests showed no significant admission-quarter differences after correction. Full descriptive results appear in Table 4 and Figure 3 for trends.

Satisfaction With Care Received

Proportions reporting happiness with care were consistently high: 95% (18/19) at admission, 79% (15/19) at Q1, 90% (17/19) at Q2, 90% (17/19) at Q3, and 95% (18/19) at Q4. The Friedman test showed no significant differences (χ^2_4=3.75, *P*=.44). Paired Wilcoxon comparisons were all nonsignificant.

Respect and Dignity

Among 16 clients with available responses, 15 (94%) reported being treated with respect and dignity at admission, 14 (88%) at Q1, 16 (100%) at Q2, 15 (94%) at Q3, and 16 (100%) at Q4. The Cochran Q test indicated no significant differences (Q(4)=4.00, *P*=.41). McNemar exact admission-quarter comparisons were all nonsignificant after Bonferroni correction.

Unmet Need for Personal Assistance

Unmet need was rare, with proportions of 5% (1/19) at admission, 10% (2/19) at Q1, 5% (1/19) at Q2, 5% (1/19) at Q3, and 5% (1/19) at Q4. The Cochran Q test revealed no significant differences (Q(4)=4.00, *P*=.41). McNemar tests were nonsignificant.

Unmet Need for Medical Care

At admission, 25% (5/20) of clients reported an unmet medical care need. This proportion declined over time to 20% (4/20) at Q1, 5% (1/20) at Q2, 5% (1/20) at Q3, and 0% (0/20) at Q4. The Cochran Q test indicated a significant decline across time

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(Q(4)=10.44, *P*=.03). However, none of the McNemar admission-quarter comparisons reached significance after correction. Trends are displayed in Figure 3.

Choice and Control of Daily Activities

Mean choice-and-control scores were close to the maximum of 6 at all time points (Table 4). A Friedman test was not significant (χ^2_4=4.56, *P*=.34). Pairwise Wilcoxon tests were nonsignificant after correction.

Sleep Quality

At admission, 16 of 19 (84.2%) clients reported good sleep. Proportions remained high, with 84.2% (16/19) at Q1, 89.5% (17/19) at Q2, and 94.7% (18/19) at both Q3 and Q4. The Friedman test showed no significant differences across time (χ^2_4=7.56, *P*=.11). Pairwise Wilcoxon tests were nonsignificant after correction.

Discussion

Principal Findings

This study examined older and disabled adults enrolled in the ASSETs for AIP program following transition from nursing homes to the community in Missouri. We observed no statistically significant decline in measures of physical functions (ie, ADLs and IADLs) and cognition across follow-up, while the QoL indicators were generally high across assessment periods. The only domain showing a statistically detectable change was unmet medical need, which declined from 25% (5/20) at admission to 0% (0/20) by quarter 4, indicating a reduction in reported unmet care needs over time. These findings support the feasibility of technology-enabled care coordination following nursing-home discharge and suggest that clients maintained function, cognition, and QoL over follow-up.

Comparison With Prior Work

Prior research on postdischarge older adults often shows progressive decline in ADL and IADL function [50,51]. In our cohort, no statistically significant decline in functional outcomes was observed over the follow-up periods. Given the small sample and absence of a comparison group, caution in interpretation is required, as it was not possible to establish if observed longitudinal patterns were attributable to real-time monitoring or to care coordination activities. Similarly, no statistically significant decline in cognitive outcomes was observed in this cohort, although the study was not powered to detect small changes over time.

Unlike other established programs, the ASSETs for AIP program combined sensor data with a care coordination team, comprised of a RN, an OT, and a SW, who reviewed individualized data dashboards daily to identify deviations in activity, sleep, or physiological patterns and coached clients as to reasonable next steps. This “human-in-the-loop” approach transformed passive data collection into actionable insights. Deviations from clients’ established daily activity patterns triggered follow-up phone calls from care coordinators to investigate causes for change and coach clients to seek additional services when indicated. Commonly recommended services included health care services, mental health services, physical therapy, social assistance, durable medical equipment resources, and home modification services.

In contrast to studies emphasizing loss of autonomy or satisfaction when transitioning home, no statistically significant decline was observed across all major QoL domains. Participants reported high satisfaction and dignity scores, suggesting that the integration of continuous monitoring and structured care coordination did not compromise person-centered care. Care coordination activities informed by assessment, sensor, and wearable data included patient education, goal setting, reinforcement of positive health behaviors, and self-advocacy training. In this sense, ASSETs for AIP align with the emerging paradigm of digitally augmented care, where continuous monitoring supports, but does not replace, therapeutic human engagement [52].

The integration of sensor data with a comprehensive, interdisciplinary team is an emerging area focused on transforming health care from a visit-centric model to a continuous, preventative care model [53-55]. Since the study’s inception, remote physiological monitoring (RPM), remote therapeutic monitoring, and AI-driven predictive health platforms have emerged from a variety of clinical and commercial offerings [54,56,57]. Overall, the prior studies suggest that technology-enabled monitoring integrated with interdisciplinary care coordination may support care delivery across a range of settings.

Implications

Implications for research, policy, and practice emerge from these findings. Integration of sensor data with care-coordination workflows demonstrates that low-cost, open-source technologies can be effectively deployed in real-world aging contexts. Given the modest sample size (n=19) and the age distribution of participants (40-80 years), these findings should be interpreted as preliminary and may not generalize to broader aging populations, particularly adults over 80 years. Future research should evaluate this approach in larger, more age-diverse cohorts to establish its applicability across different populations and care settings. Future work should use causal designs that fit real-world rollout (eg, cluster randomized trials) to rigorously test effectiveness while allowing phased implementation. There is also a need to define and validate digital biomarkers from sensor data, such as changes in mobility or nocturnal bathroom trips, that can serve as early warning signals of health decline [58]. At the policy level, findings highlight the importance of broadband access as a health intervention, since connectivity is foundational for real-time monitoring and follow-up in rural areas. Equally important is developing reimbursement pathways that align sensor-based monitoring and care coordination with existing remote monitoring and care management payment streams to support sustainability [59,60].

From an implementation perspective, several factors contributed to the practical operation of the ASSETs for the AIP model. First, the program relied on cost-feasible technologies, including open-source software, consumer-grade devices, and low-cost computing infrastructure, which reduced barriers to deployment and long-term maintenance. Second, technology was integrated into existing interdisciplinary care coordination workflows

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rather than functioning as a stand-alone monitoring system. Sensor and wearable data served as an additional source of information to support decision-making by nurses, OTs, and SWs. Finally, broadband connectivity and ongoing technical support remained important implementation considerations, particularly for rural and underserved populations. Future work should evaluate implementation outcomes such as adoption, acceptability, scalability, and sustainability to better understand how digitally enabled care coordination programs can be integrated into routine community-based care.

For practice, clear alert management protocols are essential to ensure that sensor signals translate into timely and appropriate action, with thresholds and escalation ladders that distinguish routine checks from urgent interventions. Closed-loop coordination, where every alert generates a task with an assigned owner and documented resolution, can build accountability, reduce missed follow-ups, and provide measurable outcomes for teams supporting AIP.

Limitations

These findings should be interpreted with consideration of limitations. The modest sample size, with outcome-specific analytic samples ranging from 16 to 20 participants, reduces statistical power and may mask subtle changes, particularly when only a few clients shift status between time points. The age distribution, with 6 participants aged 40-60 years and 13 aged 61-80 years, further limits generalizability, particularly to adults aged older than 80 years. Future studies should include larger samples with broader age representation to evaluate whether these findings generalize across older adult populations. The absence of a control group prevents causal inference, underscoring the need for future studies that include a comparison arm using traditional monitoring approaches. Several outcomes (ie, life satisfaction and living arrangements) on QoL showed ceiling effects, with most clients reporting the highest possible levels of satisfaction or autonomy at baseline, leaving little room for improvement. Statistical sensitivity was limited by the small sample and the use of conservative corrections, meaning that some nonsignificant findings should be interpreted as insufficient evidence of change rather than definitive evidence of stability. The aggregation of participant-level data into cohort-level means also does not account for within-person variation over time, further limiting statistical inference from the observed longitudinal patterns. Sensor data completeness was also affected by connectivity gaps, and technology acceptance varied across clients, both of which may have influenced outcomes.

Conclusions

This descriptive study of the ASSETs for AIP project demonstrates the feasibility of an innovative digital health program that relies on a team comprising a nurse, OT, and SW to deliver remote care coordination services enabled by cost-feasible and sustainable open-source and consumer-grade technologies. Specifically, the technology-enabled approach allowed care coordinators to reach clients across geographic distances, while smart home and wearable sensor data provided additional information to support decision-making. In addition, our pilot findings provide preliminary descriptive information regarding quality-of-life, functional, and cognitive outcomes among clients enrolled in the ASSETs for AIP program. Future larger studies are needed to evaluate effectiveness, implementation outcomes, and long-term sustainability while refining data-driven care coordination workflows for underserved populations.

Acknowledgments

We acknowledge the support of Tessa Wells from the University of Missouri Strategic Proposal Development Service for assistance with figure design. We also acknowledge the contribution of Gracey Jerusadan, MSN, for reviewing the results and compiling tables.

Funding

This study was supported by the US Department of Health and Human Services through the ASSETs for Aging in Place demonstration project (Missouri Department of Social Services and Centers for Medicare and Medicaid Services; 1LICMS300153 and 0069078). The funder had no involvement in this study's design, data collection, analysis, interpretation, or the writing of this paper.

Data Availability

The data used in this study were collected under a demonstration project funded by the US Department of Health and Human Services. The project was not designed for data sharing, and the data are subject to legal and regulatory restrictions. Therefore, the data are not publicly available.

Generative AI Use

The authors declare that generative AI was not used in the preparation of this manuscript.

Authors' Contributions

BR and LP conceptualized the project and methodology, led funding acquisition, and administered all aspects of the project. All authors were involved in project implementation and data collection. KL led the data analysis and wrote the original draft. SB,

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E Conrow, E Curtis, and ARD were involved in project implementation and data collection. All authors participated in writing, review, and approval of the manuscript.

Conflicts of Interest

BR is cofounder and Chair of the Board of Directors for Hekademeia Research Solutions, a nonprofit organization whose mission is to support technology-based academic research. This role is an unpaid volunteer position.

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Abbreviations

ADL: activities of daily living
AHRQ: Agency for Healthcare Research and Quality
AIP: aging in place
ASSETs: Age-Friendly Smart, Sustainable, and Equitable Technologies
CAPABLE: Community Aging in Place—Advancing Better Living for Elders
CPS: Cognitive Performance Scale
HC: home care
IADL: instrumental activities of daily living

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MFP: Money Follows the Person
MMSE: Mini-Mental State Examination
MU: University of Missouri
openHAB: open-source home automation software
OT: occupational therapist
QoL: quality of life
RN: registered nurse
RPM: remote physiological monitoring
STAReD: Smart Technology for Aging and Reducing Disability
SW: social worker
TSI: Test for Severe Impairment

Edited by J Wang; submitted 15.Jan.2026; peer-reviewed by S Lin, Y Zhang; comments to author 08.Jun.2026; revised version received 19.Oct.2026; accepted 22.Oct.2026; published 24.Nov.2026

Please cite as:
Lee K, Robinson EL, Vogelsmeier A, Reeder B, Bacon S, Conrow E, Curtis E, Roberts Dulany A, Perryman E, Popejoy L
ASSETs for Aging in Place: 12-Month Descriptive Longitudinal Study of Technology-Supported Interprofessional Care Coordination After Nursing Home Discharge
JMIR Aging 2026;9:e91524
URL: https://aging.jmir.org/2026/1/e91524
doi: 10.2196/91524
PMID:

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